Human Motion Intention based Scaled Teleoperation for Orientation Assistance in Preshaping for Grasping*

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***Abstract*— In this paper, we present an algorithm that provides human motion intention based assistance to users teleoperating a remote gripper for preshaping over an object in order to grasp it. Human motion data from the remote arm is used to train a Hidden Markov Model (HMM) offline. During the execution of a grasping task, the motion data is processed in real time through the HMM to determine the intended preshape configuration of the user. Based on the intention, the motion of the remote arm is scaled up in those orientation directions that lead to the desired configuration, thus providing the necessary assistance to the user to preshape for grasping. Tests on healthy human subjects validated the hypothesis that the users are able to preshape quicker and with much ease. Average time savings of 36% were obtained.**

I. Introduction

There has been a lot of research on service robots for carrying out activities of daily living (ADL). For all the ADLs, grasping is one of the most important tasks. Autonomous grasping, also known as grasp planning or grasp synthesis, is a widely researched area [1]-[3]. Autonomous grasping is a time consuming and a computationally intensive process. This problem is mainly due the high dimensionality of the search space over which an optimization of the grasp criterion is carried out [4]. Ciocarlie and Allen [4] demonstrated that a human input can reduce the time it takes for an autonomous planner to compute a robust grasp. In their work, the human preshaped a gripper at a point around the object and the planner computed a locally optimized grasp. This way, they reduced the problem from a global to a local optimization one. Their method took less than 2 seconds to compute a force closure grasp which was far quicker than the autonomous planners. Human knowledge and cognitive abilities can determine initial poses that lead to a robust grasp better and faster than the most advanced grasp planners. In their work, a human hand would manually preshape the electronic gripper around the object. In an actual setting using a service robot, the gripper will be teleoperated by a human user. Teleoperation is a mentally and physically challenging activity [5], [6]. Due to mapping and scaling issues, teleoperation leads to errors in motion. Errors occur while translating as well as orienting the remote arm. It makes the process time consuming and leads to frustration on the part of the user. Preshaping involves various rotations of the gripper which are challenging to execute. Orienting the remote arm gripper, so that it is at a convenient configuration for grasping an object of interest, is the one of most difficult sub-tasks [7].

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In this work, we provide orientation assistance to a user teleoperating to preshape a gripper for grasping an object. The assistance is in the form of direction based scaling in which the components of orientation that lead to the desired configuration are scaled up while those that cause deviation of the gripper from the desired configuration are scaled down. This concept of scaled teleoperation was first introduced [8] for assistance in translation. We have applied it for assistance in orientation. We propose that our method would enable the user to teleoperate the gripper to the desired configuration with fewer errors, faster and with much ease. The desired configuration is determined by recognizing the intention of the user, i.e. to what specific preshape configuration the user would like to align the gripper to. This intention is recognized using a Hidden Markov Model (HMM) that is trained offline from the user's data. Once the gripper is preshaped, the object can be either grasped directly or an autonomous planner can perform a local search to find an optimum grasp posture. The novelty of this work lies in providing motion intention based assistance in orientation to a user teleoperating an arm to preshape over a desired configuration on an object.

Previous studies have used HMM theory to determine human intention for automatically segmenting a teleoperation task but none that provide intention based assistance in orientation for grasping an object having multiple grasp configurations. Hannaford and Lee [9] were the first to use HMM to segment a teleoperation task into sub-tasks using end-effector force data. Yang et al. [10] used HMM theory to learn human skills employed in a teleoperation task and for gesture recognition. Yu et al. [11] applied a virtual fixture, an attractive field or a repulsive field depending on the task viz. following a trajectory, aligning with a target or avoiding an obstacle. Li and Okamura [12] switched a virtual fixture on or off depending on the task viz. following a path or avoiding an obstacle. Both [11] and [12] employed HMM for sub-task modeling and recognition and the operator performance was found to have improved. Aarno et al. [13] used HMM to identify the trajectory being followed so that a virtual fixture could be applied in the identified direction. This provided appropriate assistance to the user.

II. Motion Intention Recognition using a Hidden Markov Model

A Hidden Markov Model is a type of statistical model that models a stochastic process. Originally introduced in the 1960s by Baum and his colleagues [14], they have been applied to a number of real-world processes like speech

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recognition. Our process of teleoperating to a desired orientation is stochastic in nature. The randomness of our process comes from the fact that a human will produce errors in motion when trying to orient the gripper to a desired orientation. Even in the simple case of following a linear trajectory in teleoperation, the user deviates from it unless guided by a virtual fixture. The errors in the case of orientation are more pronounced. We need a model that models these errors and generates a likelihood (or probability) of a desired orientation out of several possible ones that the user is trying to teleoperate to. HMM is the stochastic model of our choice because of its already successful application in the field of teleoperation [9] - [13].

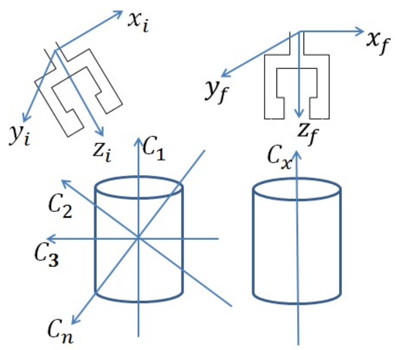

Fig. 1: Desired grasp configurations along various axes for an object

Consider the object shown in Fig. 1. There are a number of possible grasp configurations for grasping the object - one along each alignment vector $C_1, C_2, C_3, \ldots C_N$ as shown. If we consider orthogonal grasps [3], [15], for a grasp along an alignment vector C_x, the z-axis of the gripper frame, z_i will need to be aligned with C_x.

Let k be the magnitude of the projection of z_i on C_x.

$$k = z_i . C_x . \qquad (1)$$

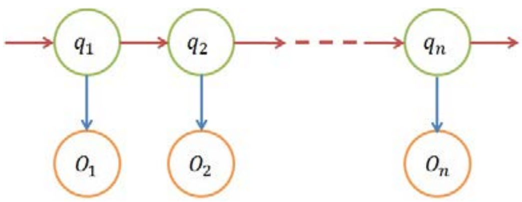

Fig. 2: Graphical representation of a Hidden Markov Model

Consider a process of N discrete states and M discrete observation symbols. Let, $S = [S_1, S_2, S_3, \ldots S_N]$ represent the states, which are hidden. Let q_t be the state at a particular time instant t. Let, $V = [O_1, O_2, O_3, \ldots O_M]$ represent the observation symbols, which are visible as observations. The states change based on a probability distribution and a state at particular time instant is only dependent on its predecessor state. The observation at a particular time instant is only dependent on the state at that time instant and both are related by a probability distribution. An HMM for such a process is shown diagrammatically in Fig. 2 and is defined by the following parameters.

- Initial State Distribution, $\pi = \{ \pi_i \}$ where

$$\pi_i = P[q_1 = S_i], \qquad 1 \leq i \leq N \qquad (2)$$

- State Transition Probability Distribution, $A = \{ a_{ij} \}$ where

$$a_{ij} = P[q_{t+1} = S_j | q_t = S_i], \qquad 1 \leq i,j \leq N \qquad (3)$$

- Observation Symbol Probability Distribution at state j, $B = \{b_j(k)\}$, where

$$b_j(k) = P[v_k \text{ at } t | q_t = S_j] \qquad 1 \leq j \leq N, \quad 1 \leq k \leq M \qquad (4)$$

For the case in which the observations are continuous, B is computed as a probability density function (PDF),

$$b_j(O) = \mathcal{N}(O, \mu_j, \Sigma_j) \qquad (5)$$

where O is the observation vector being modeled, $\mathcal{N}$ is a PDF, usually a Gaussian [16], μ_j is the mean, and Σ_j is the covariance for the distribution for jth state.

Once a model is defined, it can be used to solve three basic problems [16], viz.: the evaluation of the probability of a sequence of observations given a specific HMM; the determination of the best sequence of model states; and the adjustment of model parameters to best account for the observed signal.

In our implementation, each grasp configuration along a vector C_x (Fig. 1) represents one state. To determine the intended final orientation of the user, we need to determine the most likely state at each time instant as the user teleoperates. Thus, we will be solving problem 2 of the HMM using Viterbi decoding [16]. The observation vectors, O in our case, are the projections determined using (1). Since these values are continuous, we will be using (5) and Gaussian probability density function for determining observation probabilities. Our observation vectors at each time instant will be of the order NX1 since the z-axis of the gripper frame will be projected on all the N vectors at each time instant.

1) Estimating HMM parameters

In order to develop an HMM, its parameters viz. π, A and B need to be estimated. In our case, we assume that the user can start orienting from any of the available desired configurations. Thus, all the configurations have equal initial probability values. For N states, we have $\pi = [1/N, 1/N \ldots 1/N]$ and it is of order Nx1. If a sensor can determine obstacles because of which a few of the configurations are impossible to achieve, then those elements in π can be made to be equal to zero.

We also assume that the user normally adheres to a particular desired configuration throughout a grasping task. For this reason, we assume high values for the diagonal elements of the state transition matrix A. This is a natural assumption because humans normally adhere to their chosen orientation for a particular grasp. Thus, matrix A can be written as:

$$A = \begin{bmatrix} 0.9 & 0.1/(N-1) & \cdots & 0.1/(N-1) \\ 0.1/(N-1) & 0.9 & \cdots & 0.1/(N-1) \\ \vdots & \vdots & \ddots & \vdots \\ 0.1/(N-1) & 0.1/(N-1) & \cdots & 0.9 \end{bmatrix} \quad (6)$$

Alternatively, the value of A can also be estimated by training, i.e. by running several trials and determining the likelihood of the user changing their intention for a task once they begin executing it.

Our observation probability distribution being Gaussian, we need to estimate μ_j and Σ_j for every state j. Observation vectors O, generated from preshaping over each configuration are used to estimate the parameters μ_j and Σ_j as follows:

Let $O_1, O_2, \ldots\ O_\tau$ be the observation vectors. Let, $K = [O_1, O_2, \ldots O_\tau]$ and let $I = [1, 1, 1, \ldots 1]^\tau$, where I is a τx1 vector of ones. Here, τ is the number of observation vectors from training data for a state j. Then,

$$\mu_j = \frac{1}{\tau}\ K\ I \quad (7)$$

Let, $X = K - \mu_j I^\tau$ be the deviation of the observations from the mean. Then the covariance matrix Σ_j is computed as,

$$\Sigma_j = \frac{1}{\tau} X\ X^\tau \quad (8)$$

Similarly, we compute μ_j and Σ_j for all the remaining states.

2) Determining the Optimal State Sequence

After the HMM parameters have been estimated, the next step is to determine the intention of the user from the observations. Since the intention or the desired configuration are the states of the HMM, we solve for determining the optimal state sequence given the HMM and the observations. For this we use the Viterbi decoding [16].

III. Assistance in Orientation using Scaled Teleoperation

After we determine the desired grasp configuration from the Viterbi decoding, we apply scaled orientation teleoperation to achieve assistance.

Let R_i^O and R_f^O represent the initial and final orientations of the gripper frame with respect to the robot base frame at each time instant as the arm is moving.

$$R_i^O = \begin{bmatrix} n_{x_i} & o_{x_i} & a_{x_i} \\ n_{y_i} & o_{y_i} & a_{y_i} \\ n_{z_i} & o_{z_i} & a_{z_i} \end{bmatrix} \text{ and } R_f^O = \begin{bmatrix} n_{x_f} & o_{x_f} & a_{x_f} \\ n_{y_f} & o_{y_f} & a_{y_f} \\ n_{z_f} & o_{z_f} & a_{z_f} \end{bmatrix} \quad (9)$$

The angular velocity of the gripper frame is given by [17] as:

$$\omega_i = \frac{1}{2}\ (n_i \times n_f + o_i \times o_f + a_i \times a_f) \quad (10)$$

Ordinarily, ω_i is determined from the master device and is sent to the arm control program to move the remote arm.

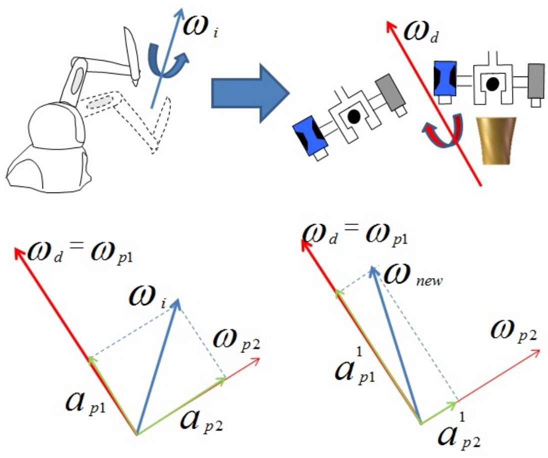

Fig. 3: Concept diagram of scaled teleoperation applied to orientation

Let ω_d be the desired angular velocity for orienting the gripper from its current frame to the desired object frame (refer to Fig. 3), the latter being determined from the intention recognition algorithm. Let ω_{p1} be the unit vector in the direction of ω_d. Let, ω_{p2} and ω_{p3} be unit vectors perpendicular to ω_{p1} such that the three form a Cartesian triad. Let a_{p1}, a_{p2} and a_{p3} be the vectors generated as a result of the projection of ω_i onto ω_{p1}, $\omega_{p2}$and ω_{p3}.

$$a_{p1} = \omega_i . \omega_{p1},\ a_{p2} = \omega_i . \omega_{p2},\ a_{p3} = \omega_i . \omega_{p3} \quad (11)$$

In order to implement scaled teleoperation in orientation, we need to scale up those components of gripper angular velocity (given by (10)) which are along the direction of the desired angular velocity, and scale down those components which are in the directions along the perpendiculars to the desired. In other words, components of ω_i in the direction of ω_d are scaled up, while those along ω_{p2} and ω_{p3} must be scaled down. Let, a'_{p1}, a'_{p2} and a'_{p3} be vectors such that,

$$\begin{aligned} a'_{p1} &= s_{up}\ a_{p1} \\ a'_{p2} &= s_{down}\ a_{p2} \\ a'_{p3} &= s_{down}\ a_{p3} \end{aligned} \quad (12)$$

where s_{up} is a scalar of a relatively higher value than s_{down}. The difference depends on the amount of assistance to be provided to the user. The higher the difference the faster the user is able to align the gripper with the desired configuration. Finally, the angular velocity that needs to be sent to the arm control program to move the arm with scaled orientation is given by,

$$\omega_{new} = a'_{p1} + a'_{p2} + a'_{p3} \quad (13)$$

IV. Experiments

The experiments were conducted in two parts. The first part involved, training and testing of the HMM and intention based scaled teleoperation method was validated in the second part.

The complete test-bed is shown in Fig 4. A 6 degree of freedom (DOF) Phantom Omni device [18] was the master and an in-house developed 7 DOF wheelchair mounted robotic arm (WMRA) [19] system was the slave. A parallel-jaw gripper was mounted on the end-effector of the arm. The wheelchair was stationary throughout the experiments and movements of only the arm and the gripper were used. Cartesian mapping, joint limit avoidance and singularity avoidance have been implemented and tested on the arm for ease of teleoperation.

Fig. 4: Test-bed consisting of the master device, the robotic arm with gripper mounted on it and the object to be grasped

A commonly available camera tripod was used as the object to be grasped. It was our object of choice due to a variety of grasping configurations possible on its parts like the mounting plate, various knobs, handles etc. Specifically, we focused preshaping for grasping the tilt release knob and the mounting plate (refer to Fig. 5). The two parts gave us a good range of rotational movements of roll, pitch and yaw for testing our orientation assistance concept.

Fig. 5: The gripper in the desired preshaping configurations for grasping the tilt release knob and the mounting plate of the tripod

It is important to note that in this work we are only concerned with preshaping for grasping and not actually grasping the object. Force-closure grasps, finding optimal grasping points etc. are out of the scope of this work. We limited our work to aligning the gripper with the object and assisting the user to do so using intention based scaling. The accuracy of aligning is determined by the experiment supervisor or human observation.

Five subjects were used for testing on the system. They were all males, aged 24 to 40 years and with no experience in teleoperating a robotic arm. Each subject familiarized with the system before they began with their trials. All the subjects were quick in learning the skills needed to teleoperate and could teleoperate the arm after 2 trials. They could translate and orient the arm in all the possible directions, and could satisfactorily preshape the gripper over the different parts of the tripod.

A. *HMM Development*

As mentioned earlier, we focused on preshaping to grasp the mounting plate and the tilt release knob. Thus, our HMM has two states viz. preshape configuration over the tilt release knob and the one over the mounting plate. Our observation vector has two elements viz. projection of the gripper z-axis on the alignment vectors C_x (refer to (1)) for the two parts of the tripod. Let, C_1 be the alignment vector for the tilt knob, and C_2 for the mounting plate. In this proof of concept, C_1 and C_2 were determined offline by aligning the gripper with the part such that it results in an orthogonal grasp. The -ve of the gripper z-axis then gave us C_1 and C_2. In an actual setting, these alignment vectors could be determined by using a depth based vision system, such as Microsoft Kinect. Such a system would give the alignment vectors in the form of principal axes of the object parts after reconstructing them. Our state transition vector is assumed to be $A = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$ and our initial probability distribution is, $\pi = [0.5 \ 0.5]$ based on the assumptions mentioned previously in Section II.

1) *Training the HMM*

As mentioned earlier, μ_j and Σ_j are the parameters that need to be determined in order to develop our HMM. For this, we collected training data from the subjects in the form of observation vectors O. Each subject is asked to teleoperate the gripper to preshape for grasping each object part 10 times starting at a different gripper pose every time. These datasets were combined for each preshape. (7) and (8) were applied on this combined dataset to determine, μ_j and Σ_j for each preshape or state. The number of trials, 10, was randomly chosen. Lesser trials may have given approximately the same parameter values but this was not analyzed.

2) *Testing the HMM*

We collected test data from subjects in the form of observation vectors over 10 trials for each preshape configuration. The subjects were asked to preshape to the desired configuration starting from random initial poses that were close to the desired configuration for 5 of the trials, and starting from random initial poses not close to the desired for the other 5 trials. This way, a good range of starting poses were taken into account. Viterbi decoding over the training data was used to determine the average time per subject per preshape configuration to detect the right intention.

B. *Comparison of Intention based Scaled Teleoperation with Unassisted Teleoperation*

In order to determine the user intention in preshaping to a desired configuration, the observations vectors generated as a result of teleoperation were processed through the Viterbi algorithm. Based on the intention, scaling in the appropriate direction was provided to the user to assist in preshaping. In this implementation of the Viterbi algorithm, we took the average of the intention values generated over the last 100 time instances to determine the overall intention. The logarithm of the probability values were used in order to avoid data underflow issues which can occur due to low probability values. The scaling values chosen to be 3 and 0.2 for s_{up} and s_{down} respectively (refer to (12)).

The subjects were asked to teleoperate the gripper to preshape over the tilt knob and the mounting plate in two modes viz. without any intention recognition or assistance and with intention based orientation assistance. For each mode and object part, each subject executed the preshaping task six times. Each time, random initial poses were selected. For the intention based assistance modes, the user had the option of activating scaled assistance or deactivating it by toggling a keyboard key. They would deactivate when the system would detect a wrong intention and would otherwise activate it. This gave the user the ultimate control of the arm and avoided their motion being scaled to the wrong preshape. In 3 out of the 6 trials for each subject and object part, they were asked to change their intention midway during the task and preshape the other part. This test case would determine the robustness of the intention based scaling versus unassisted mode. In a real-life setting, this action can be viewed as the user changing intention due to not being able to grasp from a certain configuration. In all, each subject performed 24 trials. The average time it took for each subject to complete a preshape task and the gripper orientations during teleoperation were recorded.

V. RESULTS AND DISCUSSION

Fig. 6 shows the average number of frames it took for the intention recognition algorithm to detect the right intention per subject per object part, averaged over all trials. Each frame is equivalent to one run of the Viterbi algorithm, which ran at approximately 450 Hz. Standard errors have also been determined and are shown in the figure.

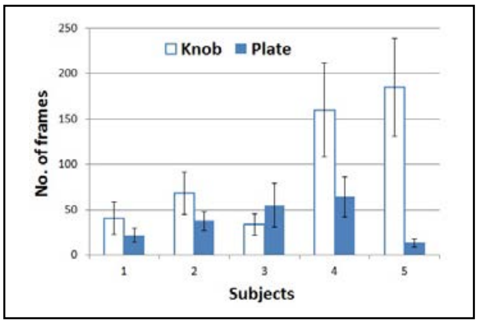

Fig. 6: Average number of frames to detect the right intention when preshaping over the knob and the plate

From the figure we can see that the time the system took to detect the right intention is different for different subjects. This is because it depends on a lot of factors like the speed at which the subject teleoperates, stating pose, skill level of the subject etc. No analysis was conducted to determine the effect of any of these parameters on the speed of intention detection. We also see that the detection was quicker for the plate. This indicates that it might have been easier and quicker for the subjects to orient over the plate but no statistical results were generated to confirm this.

The average time per subject to complete a preshape task in both the modes for the knob and plate is presented in Fig. 7 and 8. For these tests, the subjects began teleoperating from random initial poses and preshaped over a particular object part.

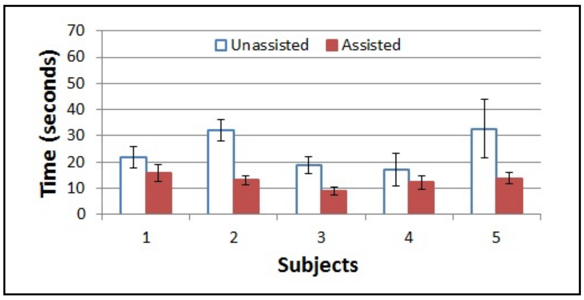

Fig. 7: Time plots comparing intention based assistance with unassisted teleoperation when preshaping over the knob from random initial pose.

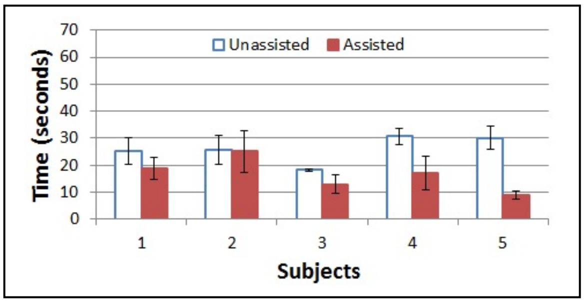

Fig. 8: Time plots comparing intention based assistance with unassisted teleoperation when preshaping over the plate from random initial poses.

From the two figures, it is clear that intention based assistance enables the subjects to complete the task much faster. Percentage difference in the time per subject per preshape task was determined as the fraction of the difference between the average times in the two modes, over all trials. This value averaged over all subjects is the average percentage time difference in the two modes per preshape task. For knob preshape task, it was 45%, and it was 34% for the plate preshape task.

Fig. 9 and 10 show the time results when the subjects were asked to preshape over an object part and then while they were in the process of doing so, were asked to preshape over the other object part.

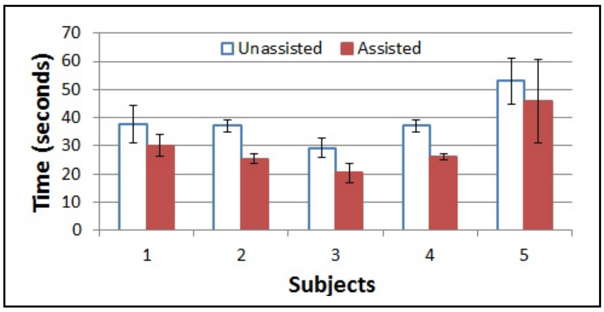

Fig. 9: Time plots comparing intention based assistance with unassisted teleoperation. The subject was asked to preshape over the knob while in the process of preshaping over the plate

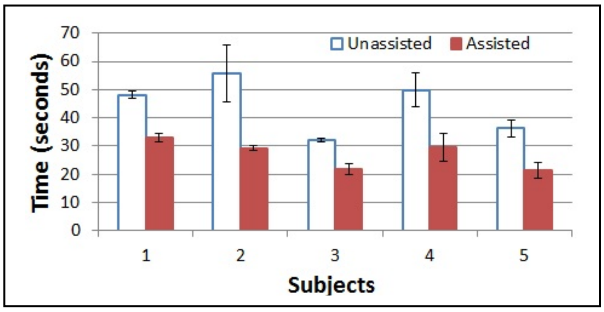

Fig. 10: Time plots comparing intention based assistance with unassisted teleoperation. The subject was asked to preshape over the plate while in the process of preshaping over the knob.

The intention based assistance enabled the user to preshape quicker. Average percentage difference in time for the knob preshape task was 25% while it was 39% for the plate preshape task.

The subjects found the intention based orientation assistance very useful in aligning with the target in teleoperation. It made the aligning task much easier to perform, and they preferred it over the unassisted teleoperation mode. A common feedback from the subjects was that the method made rotations very easy. With the intention based assistance mode, the subjects had to make fewer movements. Also, fewer deviations were observed by the subjects from their orientation paths when performing preshaping with intention based assistance. This was naturally expected since the motion was scaled up in the desired directions. Some subjects, however, did overshoot when aligning the gripper with the target, and others found using the keyboard key to switch assistance mode on and off as annoying. According to their feedback, it diverted their attention from the gripper movements.

VI. Conclusion And Future Work

In this work, we have demonstrated that intention based assistance improves the task performance in preshaping around an object. Human subjects found the assistance in orientation very helpful, and according to their feedback, it made the preshaping task much easier for them to execute in teleoperation. This combined with intention recognition further sped up the task execution. Average percentage difference over all tasks for all subjects was 36%.

While the results are promising, further improvements and validations are needed to realize the benefits of the methodology. The next step will be to use more concepts from the HMM theory and apply the algorithm to general indoor objects with multiple preshape configurations. We will evaluate if the extended algorithm is able to determine the object of interest and the intended human preshape configuration on that object when a number of such objects are placed in the environment. For this extension, increasing the dimensions of the feature vector by including projections of incremental translation vectors will be needed. Integrating a depth based vision system that estimates the shape and pose of novel objects will preclude the need to use predetermined grasp configurations for testing. Statistical analysis of data from experiments is part of the future work.

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References

[1] K. B. Shimoga, ‘Robot Grasp Synthesis Algorithms: A Survey’, International Journal of Robotics Research, vol. 15, no. 3, pp. 230-266, 1996.

[2] Sahbani A., El-Khoury S. and Bidaud P., ‘An Overview of 3D Object Grasp Synthesis Algorithms’, Robotics and Autonomous Systems, vol. 60, No. 3, pp.326-336, 2012.

[3] Miller A., Knoop S., Christensen, H. and Allen P., ‘Automatic Grasp Planning Using Shape Primitives’, IEEE International Conference on Robotics and Automation, Taiwan, 2003

[4] Ciocarlie M. and Allen P., ‘Hand Posture Subspaces for Dextrous Robotic Grasping’, International Journal of Robotics Research, 2009.

[5] DeJong B., Colgate J. and Peshkin M., ‘Mental Transformations in Human-Robot Interaction’, Intelligent Systems, Control and Automation: Science and Engineering, Springer, Vol. 1010, pp. 35-51, 2011.

[6] DeJong B., Faulring, E., Colgate J. and Peshkin M., ‘Lessons Learned from a Novel Teleoperation Testbed’, Industrial Robot: An International Journal, Volume 33, Number 3, pp. 187-193(7), 2006.

[7] Khokar K., Reed K., Alqasemi R. and Dubey R., ‘Laser-assisted Telerobotic Control for Enhancing Manipulation Capabilities of Persons with Disabilities’, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2010.

[8] Pernalete N., Yu, W., Dubey, R. and Moreno W., ‘Augmentation of Manipulation Capabilities of Persons with Disabilities using Scaled Teleoperation’, IEEE International Conference on Intelligent Robots and Systems, Switzerland, 2002.

[9] Hannaford B. and Lee P., ‘Hidden Markov Model Analysis of Force/Torque Information in Telemanipulaton’, International Journal of Robotics Research, vol. 10, no. 5, pp, 528-539, 1991.

[10] Yang, J., Xu, Y. and Chen C. ‘Human Action Learning via Hidden Markov Model’, IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans, vol. 27, no. 1, 1997.

[11] Yu W., Alqasemi R., Dubey, R. and Pernalete N., ‘Telemanipulation Assistance based on Motion Intention Recognition’, IEEE International Conference on Robotics and Automation, Spain, 2005.

[12] Li M. and Okamura A., ‘Recognition of Operator Motions for Real-Time Assistance using Virtual Fixtures’, 11th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, 2003.

[13] Aarno D., Ekvall S. and Kragic D., ‘Adaptive Virtual Fixtures for Machine-Assisted Teleoperation Tasks’, IEEE International Conference on Robotics and Automation, Spain, 2005.

[14] Baum L. and Petrie, T., ‘Statistical Inference for Probabilistic Functions of Finite State Markov Chains’, Ann. Math. Stat., vol. 37, pp. 1554-1563, 1966.

[15] Balasubramanium R., Xu L., Brook P., Smith J. and Matsuoka Y., ‘Human-Guided Grasp Measures Improve Grasp Robustness on Physical Robot’, IEEE International Conference on Robotics and Automation, USA, 2010.

[16] Rabiner, L., ‘A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition’, Proceedings of the IEEE, Vol. 77, No. 2, pp. 257-286, 1989.

[17] Luh J., Walker M. and Paul R., ‘Resolved-Acceleration Control of Mechanical Manipulators’, IEEE Transactions on Automatic Control, vol. AC-25, No. 3, 1980.

[18] http://www.sensable.com/haptic-phantom-omni.htm

[19] Alqasemi R. and Dubey, R., ‘Combined Mobility and Manipulation Control of a Newly Developed 9-DOF Wheelchair Mounted Robotic Arm System’, IEEE International Conference on Robotics and Automation, 2007.